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## Categorization Of Watermelon Maturity Level Based On Rind Features

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### Abstract

This paper proposed a method to determine the best capture position of the watermelon's rind for categorization of maturity level. A total of forty five watermelon samples are used specifically fifteen samples are in 60% ripeness, another fifteen samples in 70% ripeness and remaining fifteen samples in 80% ripeness. Five different positions of the watermelon which are from the top, bottom, lean, yellowish spot and best side are captured using a digital camera. The images are then analyzed using feature extraction based on RGB color components value. Each capturing positions is analyzed and comparisons are made between all five capturing position to identify the optimum capturing angle that provides significant ripeness stage. Initial results attained showed that capturing the yellowish spot of the watermelon as the best categorization features.

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**Keywords:** Watermelon; RGB; Image processing; Artificial Neural Network

### 1. Introduction

Agriculture products are being more demanding in market today. To increase its productivity, automation to produce these products will be very helpful. One of the growing agriculture products is watermelon [1]. The external appearance is one of the most important factors that affect the value of the fruits. Consumers have developed different relationships between color and the overall quality of the specific product. In the case of watermelons, for example, the consumers are attracted by the color tone and its distribution on the surface [2]. Monitoring and controlling ripeness is becoming a very important issue in the fruit industry since the state of ripeness during harvest, storage, and market distribution determines the quality of the final product measured in terms of customer satisfaction. Many methods to monitor the ripeness of fruit have already been proposed [3].

Watermelon or *Citrullus Lanatus* was found growing wild by Livingstone in 1854 [4]. Generally, watermelons are round in shape. However, most of them are not perfectly round. Moreover, the rind color distributions are also not uniform. It is hard to find two watermelons which have similar uniformity in the rind color. In order to establish a parameter of the rind for ripeness categorization, it is crucial to find the best spot or position of capturing that can provide the most reliable and distinguishable features between each ripeness stage.

Watermelons need to be ripe when harvested. Watermelon typically has 10-11% soluble solids when ripe [5]. Because individual fruits are pollinated at different times, multiple harvests are usually necessary. After harvest, growers should sort watermelons by size and check for maturity and pest damage to ensure marketing of high quality product [6].

Currently, the use of image processing technique has gained much interest. One of the most popular usages is to detect and extract desired object from its background. The reason of extraction is to remove unwanted objects and to simplify analysis for the desired object. In this study, the methods of removing unwanted objects and color component extraction are further explored for the categorization of the watermelon based on rind color.

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## 2. Literature Review

Susanna Buratti et al. [7] evaluated the capability of a commercial electronic nose based on a 10 sensor-array (PEN2, Aisense Analytics Inc.) to classify the fruits belonging to different cultivars and to monitor their ripening stage during shelf life from the day after harvest until fruits were senescent in their research. The performance was compared using the sensor-array with the results of classical and non-destructive techniques such as the evaluation of colour and ethylene production. The electronic nose data are analysed by PCA, LDA and CART analysis and were used to build a mathematical model for the evaluation of the ripening stage.

Next, Siti Nordiyana et al. [8] presented study using an artificial olfactory system as a non-destructive instrument to measure fruit ripeness. This system comprised of an array of semiconductor gas sensors as well as data acquisition and analysis components. Based on the study conducted, it has been proven that this electronic nose system is capable of determining fruit ripeness. The sensor array successfully left unique characteristic pattern or fingerprint for each stage of ripeness.

Further, J. Brezmes et al.[3] developed an Electronic Nose for non-destructively for monitoring the fruit ripening process. Based on a tin oxide chemical sensor array and neural network-based pattern recognition techniques, the olfactory system designed is able to classify fruit samples into three different states of ripeness such as green, ripe and overripe with very good accuracy. Based on the proposed method, classification of peaches and pears attained success rate above 92% while a slightly worse accuracy for classification of apples. An additional feature of the system is its ability to accurately predict the number of days the fruit has been in storage since harvest.

Another related research was done by Maxsim Yap Mee Sim et al. [9] that studied on a development of a disposable sensor used to monitor the ripeness process and to investigate the different maturity stages of jackfruit by chemometric treatment. Response of the sensor strip fabricated using screen printing technology was analyzed using Principal Component Analysis (PCA) and the classification model constructed by means of Canonical Discriminant Analysis (CDA) enable unknown maturity stages of jackfruit to be identified. Results generated from the combination of the two classification principles showed the capability and the performance of the sensor strip towards jackfruit analysis.

## 3. Material and Methodology

Figure 1 showed the overall process in determining the best watermelon's capture position for analyzing the maturity level. The process is divided into three main steps namely experimental setup and calibration, placement of capturing the sample, pre processing and identification the best capturing position using Artificial Neural Network (ANN).

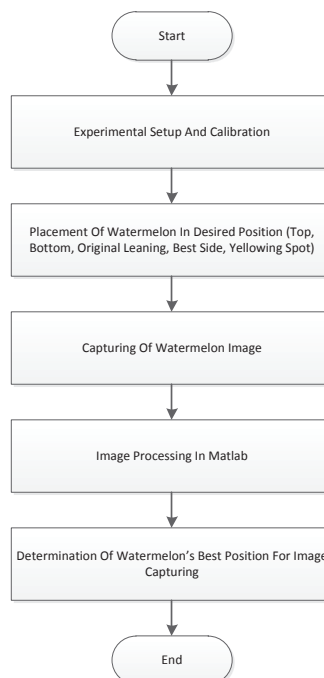


Figure 1: Overall process for determination of watermelon's best capture position to analyze the ripeness stage

### 3.1 Experimental setup and calibration

In this study, a total of 45 samples of watermelons are used. All these samples are picked by experienced farmer and categorized based on 60% maturity, 70% maturity and 80% maturity. Each category consists of 15 samples and is marked appropriately as database in this research. The experimental setup is as shown in Figure 2.

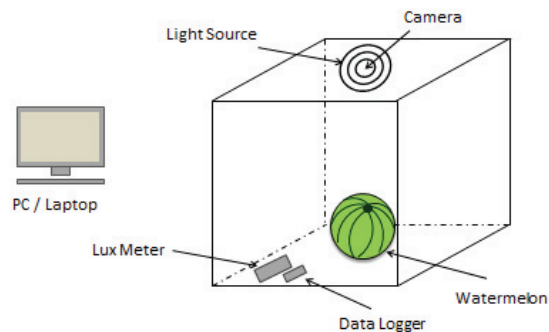


Figure 2: Experimental Setup

A ring-shaped pendaflour light is placed at the top of the light box to act as a light source. Ring shape light is chosen as it emits light more uniformly. As for the camera, it is placed inside the light ring providing excellent capturing angle and position. A light box is used in order to control the light intensity. This is done as light intensity affects heavily on RGB colour components. By having a light box, more stable light intensity can be maintained thus providing more reliable RGB data. A LUX meter is placed inside the light box to monitor the light intensity. Before testing is done, calibration of light intensity inside the light box is done to ensure stable readings. LUX meter is connected to the Data Logger and readings of the light intensity are taken every 15 minutes. Both the camera and Data Logger are connected to laptop for remote control and data transfer respectively.

### 3.2 Placement of watermelon for capturing

For capturing purpose, a Canon DSLR EOS 500D is used. Due to the nature round or oblong shape of the watermelon, five possible capture positions are determined. These capture positions are from top, bottom, original leaning, best side and yellowish spot as shown in Figure 3. It is crucial to determine the capture position as the colour and rind pattern are randomly scattered.

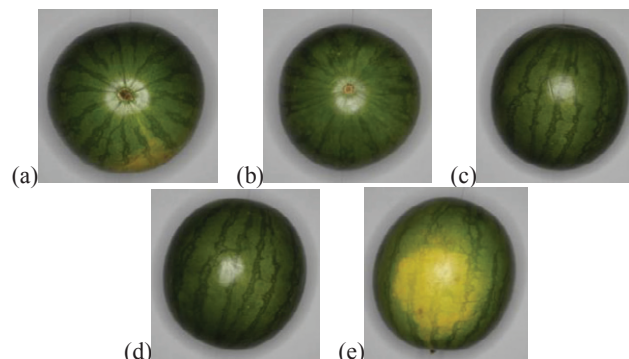


Figure 3: (a) Top, (b) Bottom, (c) Original leaning, (d) Best side, (e) Yellowish spot

### 3.3 Pre Processing of Watermelon Image

All images captured need to be pre-processed in order to suppress irrelevant information and improve image data. This is done by suppressing undesired distortions and enhancing image features that are relevant for further processing. Here, undesired background is subtracted from the image, leaving only the desired object which in this case is the watermelon. Steps involved in the pre-processing stage are image resizing, RGB to binary image conversion, morphological operation and masking.

The original image of 4752x3168 pixels is resized to 1/8 of the original size in order to minimize the number of processes and time required to analyze the image. Then, it is converted from RGB image format to binary image format. This is done as most pre-processing technique deals with binary images. Morphological operations are also incorporated as to increase the intensity of the image. Process of dilation and erosion are also done to reduce grain noises. Next, the image is analyzed to identify the watermelon to extract it from the background. This is done by scanning the image from top to bottom to find connected pixels or blobs labeled from 1, 2, 3 and so on. Each blob is also analyzed for its properties such as area and diameter. It is known that the watermelon has an area of more than 16000 pixels. In order to correctly identify the watermelon, area property is used. Blobs having area less than 16000 pixels are removed. As a result, all other objects are removed while leaving the watermelon intact. Algorithm for this operation is outlined as below:

```

BEGIN
Scan image for blobs from top to bottom
Label blobs
Compute area for each blob
If blob area less than 16000 pixels
Remove blob
Else intact blob
END

```

Final step of the pre-processing stage is image masking. The masking is performed between the original RGB image and the binary image. The aim of masking is to produce an image having only the watermelon with a black background or pixel value 0. The masked image is used during feature extraction as to categorize the watermelon according to the maturity level.

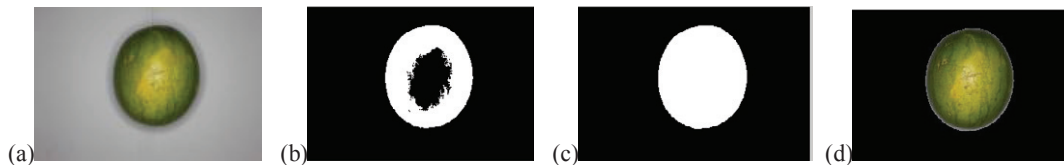


Figure 4: Image pre-processing, (a) Resized image of 1/8 of original pixels, (b) RGB to binary image conversion, (c) Morphological operation of erosion and dilation, (d) Masking between image in (c) and (a)

Once the pre-processing stage is completed, the next step is feature extraction to obtain the RGB colour component values. The sum of each colour component is calculated for each and every pixel area to compute the mean value. Background image is not included as the pixel value is 0. Only the RGB colour of the watermelon's rind is taken into consideration. Equation 1, 2 and 3 are used to extract the mean value for each red, green and blue colour component respectively. More detailed explanations can be found from reference [10].

$$\text{Red : } \mu R = \frac{\sum_{i=0}^x \sum_{j=0}^y P(x,y)}{\sum n} \times 255 \quad (1)$$

$$\text{Green : } \mu G = \frac{\sum_{i=0}^x \sum_{j=0}^y P(x,y)}{\sum n} \times 255 \quad (2)$$

$$\text{Blue : } \mu B = \frac{\sum_{i=0}^x \sum_{j=0}^y P(x,y)}{\sum n} \times 255 \quad (3)$$

### 3.4 ANN for categorization

RGB colour components value obtained from image processing are used as the features in determining the best capture position. The Red, Green and Blue components value are fed into Artificial Neural Network as input. 30 samples are used for training while remaining 15 samples are used as testing.

For the ANN architecture, three input nodes are set which are the red colour component, green colour component and blue colour component from the RGB colour space. Output nodes are set to three which each represent different level of maturity namely 60% ripeness, 70% ripeness and 80% ripeness. The training algorithm used is the Levenberg-Marquardt backpropagation with hidden layer is set to 20. Epoch range was between 1 to 15. Next, three targeted value are set specifically [100] for 60% ripeness, [010] for 70% ripeness and [001] for 80% ripeness.

## 4. Results and Discussions

This section will discuss and detail the results attained based on the proposed method. Firstly, to ensure that images of the watermelon captured are under stable lighting condition or controlled condition, a calibration is done inside the light box. Calibration is done from morning until evening. Figure 5 showed the LUX value from 9 am until 6 pm.

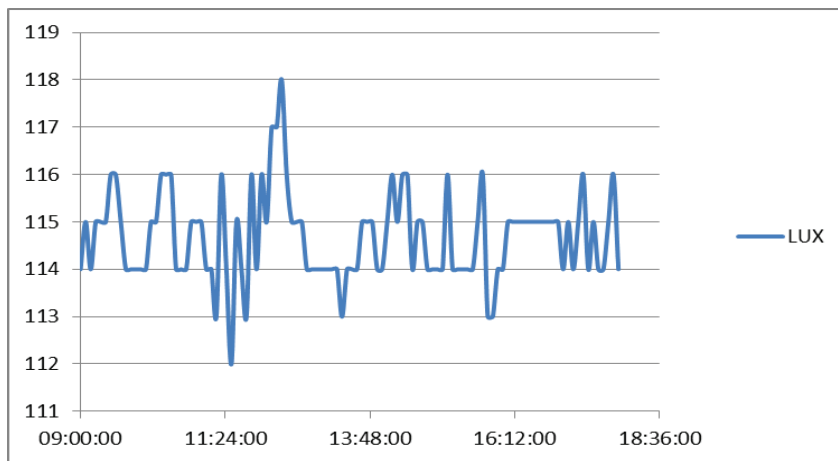


Figure 5: Calibration of light intensity inside the light box during the day

It can be seen that the light box provides stable light intensity regardless of when the calibration is done. The average lux readings are 112 Lux with tolerance between  $\pm 3$  Lux.

Further, all data extracted from the images are fed into ANN to compare the reliability and accuracy in determining the maturity level. Figure 6 showed the regression plot for both training and testing. Training regression value is ensured to be more than 0.9 for all five capturing positions to ensure significant training phase are performed. Next, the testing regression value is analyzed to determine which capturing position are the most reliable data for accurate measurement of the watermelon maturity level. As observed in Figure 5, the regression value for yellowish spot capture position is the highest which is 0.751. Second highest regression value is from top capture position at 0.702 followed by original leaning capture position 0.640. Best side capturing position resulted in regression value of 0.55232 while the least regression value is 0.19665 for bottom capturing position. Summary of regression value is as shown in Table 1 along with sum squared error value.

Table 1 : Summary of regression value for all five capturing positions

| Capture Position      | Training regression value | Training SSE value | Testing regression value | Testing SSE value |
|-----------------------|---------------------------|--------------------|--------------------------|-------------------|
| Top                   | 0.917                     | 0.433              | 0.702                    | 3.593             |
| Bottom                | 0.902                     | 0.509              | 0.197                    | 1.762             |
| Original leaning      | 0.920                     | 0.359              | 0.640                    | 0.708             |
| Best side             | 0.923                     | 0.269              | 0.552                    | 0.994             |
| <b>Yellowish spot</b> | <b>0.936</b>              | <b>0.0934</b>      | <b>0.751</b>             | <b>0.463</b>      |

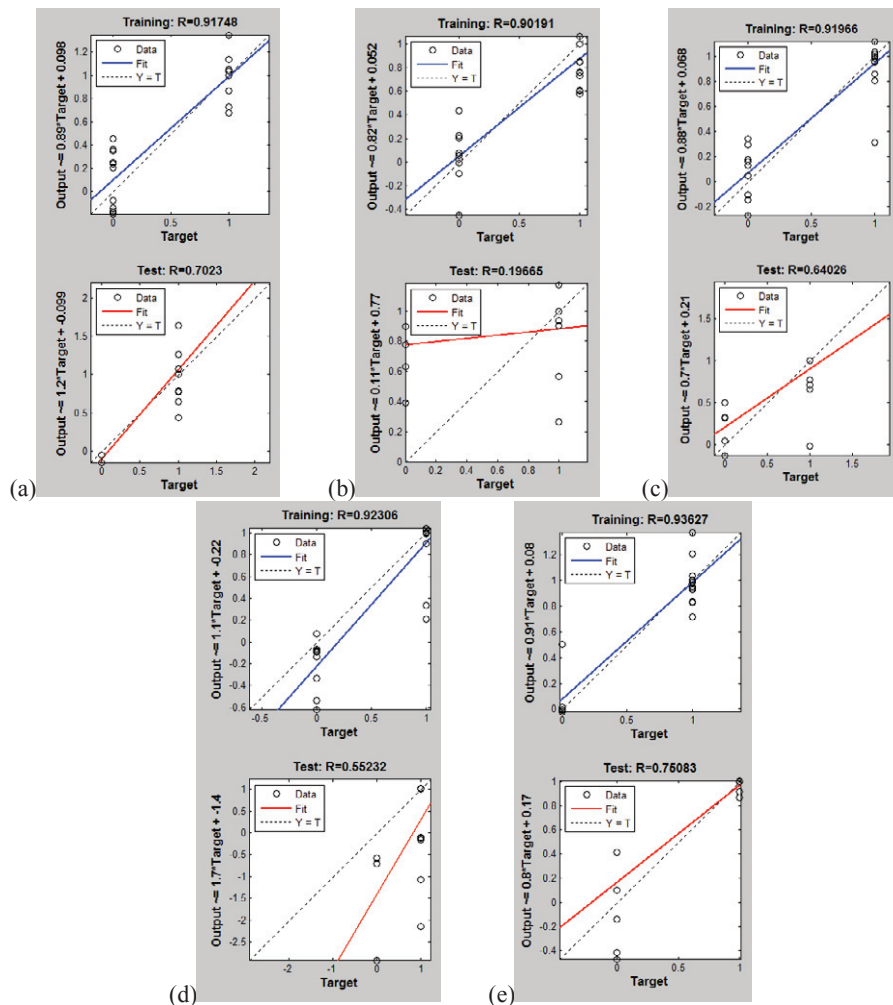


Figure 6: Regression plot for training and testing, (a) Top, (b) Bottom, (c) Original leaning, (d) Best side, (e) Yellowish spot

For testing purposes, a total of 15 samples are used. Each category of 60%, 70% and 80% consists of 5 samples. Table 2 showed the confusion matrix for the accuracy attained using Artificial Neural Network.

Based on total of fifteen testing samples as tabulated in Table 2, for top capture position a total of ten samples are correctly identified to be in the right maturity level with five samples are mistakenly categorized. Most error is from the 80% level which mistakenly recognize as 70% maturity. As for bottom capture position, it showed the worst recognition since only three samples are correctly identified. Conversely, original leaning capture position proven capable to correctly categorized nine samples. Additionally, 70% maturity level is the most mistakenly identified based on three samples wrongly categorized. Further, for best side capture position, a total of eight samples are successfully identified to be in the correct maturity level. However, none of the 80% maturity level samples managed to be correctly identified. Finally, the last capture position of yellowish spot showed that eleven samples are correctly identified thus proven to be the most reliable capturing spot. In this category, only one sample from each 60% and 70% maturity level are mistakenly identified while two samples from the 80% maturity level.

Table 2 : Confusion matrix for testing for different capture position

| Confusion Matrix Capture Position |     | Predicted     |               |               | Accuracy (%) |
|-----------------------------------|-----|---------------|---------------|---------------|--------------|
|                                   |     | 60%           | 70%           | 80%           |              |
| Top                               | 60% | 3<br>(20%)    | 1<br>(6.67%)  | 0<br>(0%)     | 66.67%       |
|                                   | 70% | 0<br>(0%)     | 4<br>(26.67%) | 1<br>(6.67%)  |              |
|                                   | 80% | 0<br>(0%)     | 3<br>(20%)    | 3<br>(20%)    |              |
| Bottom                            | 60% | 0<br>(0%)     | 4<br>(26.67%) | 1<br>(6.67%)  | 20.00%       |
|                                   | 70% | 3<br>(20%)    | 1<br>(6.67%)  | 2<br>(13.33%) |              |
|                                   | 80% | 1<br>(6.67%)  | 1<br>(6.67%)  | 2<br>(13.33%) |              |
| Original leaning                  | 60% | 3<br>(20%)    | 0<br>(0%)     | 1<br>(6.67%)  | 60.00%       |
|                                   | 70% | 1<br>(6.67%)  | 3<br>(20%)    | 2<br>(13.33%) |              |
|                                   | 80% | 0<br>(0%)     | 1<br>(6.67%)  | 3<br>(20%)    |              |
| Best side                         | 60% | 4<br>(26.67%) | 2<br>(13.33%) | 0<br>(0%)     | 53.33%       |
|                                   | 70% | 2<br>(13.33%) | 4<br>(26.67%) | 0<br>(0%)     |              |
|                                   | 80% | 0<br>(0%)     | 3<br>(20%)    | 0<br>(0%)     |              |
| Yellowish spot                    | 60% | 4<br>(26.67%) | 1<br>(6.67%)  | 0<br>(0%)     | 73.33%       |
|                                   | 70% | 0<br>(0%)     | 4<br>(26.67%) | 1<br>(6.67%)  |              |
|                                   | 80% | 0<br>(0%)     | 2<br>(13.33%) | 3<br>(20%)    |              |

## 5. Conclusion

As a conclusion, rind features can be used to categorized maturity level, This is proven based on the results that yellowish spot position provided highest accuracy rate of 73.33% followed by top capturing position that obtained 66.67% accuracy. The worst capturing position for determination of maturity stage is the bottom position with only 20% accuracy. Future work need to verify the proposed method using other machine classifier and more watermelon samples.

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